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The Copula ADCC-GARCH model can help PIIGS to fly

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ABSTRACT

Recent crises have revived the interest of researchers to investigate the economic characteristics of regions such as the PIIGS, which have been the Eurozone's most troubled economies. We show that it is possible to obtain benefits from investing in these markets by using time-varying returns and volatility forecasts from a Copula-ADCC-GARCH with structural breaks model. The results show that the use of this approach leads to a significant improvement of the Sharpe ratio when compared to the naïve strategy and the optimal portfolios based on a simple multivariate GARCH approach such as the DCC model, even when different transaction costs are considered.

1. Introduction

The analysis of time-varying linkages and co-movements between equity markets has received a great deal of attention from researchers and investors in recent years. A wide variety of methodologies have been used by researchers, not only for analyzing time-varying linkages among equity markets, but also to optimize different portfolios, see Syriopoulos and Roumpis (2009), Guidi and Ugur (2014) and Miralles-Marcelo et al. (2015) among others.

Furthermore, recent crises have revived the interest of researchers in investigating the economic characteristics and influence of specific economic regions such as the PIIGS[1] (Portugal, Italy, Ireland, Greece and Spain), BRICS (Brazil, Russia, India, China and South Africa) and MENA (Middle East and North African countries) see Samitas and Tsakalos (2013).

The objective of identifying new diversification opportunities leads us to focus our work on the PIIGS's stock markets. These countries have been the Eurozone's most troubled economies and, in theory, they are not interesting for the international investors. However, apart from Greece, they recently seem to be recovering due to improved fundamentals, rising consumer confidence and demand, booming exports and declining unemployment. These factors have been crucial in steering these economies back on their tracks. Additionally, investor confidence in these countries is increasing since in Portugal, Italy, Ireland and Spain, we find lower yields in the ten-year government bonds than the yield offered on the U.S. ten-year Treasury note on the same day. In our opinion, those facts will lead to a greater interest in these countries and, therefore, to better investment opportunities.

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[1] They are also known by the acronym of GIPSI (Greece, Ireland, Portugal, Spain and Italy) if they are ordered by the magnitude of their credit risk. This acronym was created in 2010, so the data to order them refer to that date.

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In this context, the aim of our study is to provide evidence that it is possible to obtain benefits from investing in these markets by using time-varying returns and volatility forecasts from a Copula-ADCC-GARCH with structural breaks model.

We improve the previous empirical evidence in various ways. Firstly, we consider the Copula-based Multivariate GARCH model proposed by Lee and Long (2009), the use of a semiparametric approach to estimate the cumulative distribution function (CDF) of each standardized residual series as in Harris and Mazibas (2013), and the extensions of the DCC model allowing for asymmetries and structural breaks as in Cappiello et al. (2006) and Kalotychou et al. (2014). We then merge all these multivariate techniques in a way that, to our knowledge, is used for the first time in the empirical evidence to propose the use of a Copula-ADCC-GARCH model with structural breaks.

Secondly, most of the empirical evidence based on the DCC models is focused on analyzing the time-varying correlations. However, we employ this approach for forecasting returns, variances and covariances, and solving different allocation problems. Therefore, we provide the out-of-sample performance of an optimal portfolio constructed on the basis of time-varying return and volatility forecasts from the Copula-ADCC-GARCH model with structural breaks approach. The results achieved on the portfolio optimization problems are compared with those obtained from an equally weighted portfolio, also known as naïve portfolio, following the common procedure in the previous empirical evidence.

Finally, the database used, from January 7, 1998 through December 31, 2014 comprises different financial crises in the PIIGS countries, which gives more value to the possibility of finding an approach where performance is improved.

The results show that the use of forecasted returns and volatilities from a Copula-ADCC-GARCH model with structural breaks approach for solving the optimization problems lead to a significant improvement on the portfolio performances. Moreover, we prove that there are benefits in investing in the PIIGS countries using a mean-variance strategy instead of two alternative strategies which were also considered alongside the naïve, which was the benchmark. That mean-variance strategy clearly outperforms the other ones with significant positive Sharpe ratios, even when different transaction costs are considered.

The remainder of this paper is organized as follows. In Section 2 we present a review of related literature. In Section 3 we outline the methodology employed to construct and evaluate the performance of the proposed diversification strategy. Section 4 defines the database. Section 5 shows the principal results and Section 6 provides the main conclusions.

2. Literature review

One of the most important issues in finance in recent years has been the analysis of linkages among stock markets. Aloui et al. (2011) are interested in modeling the co-exceedances of stock market returns below or above a certain threshold on those emerging countries known by the acronym of BRIC (they do not consider the South African stock market). They test for both the degree and type of their dependence at extreme levels. In order to do so, they combine different GARCH models with copula functions and extreme value theory grouping the variables by pairs. They provide evidence of extreme co-movements for all market pairs both in the left and right tails.

Dimitriou and Kenourgios (2013) examine the time-varying linkages among US dollar exchange rates in five currencies. They employ a Multivariate FIAPARCH (1,d,1)-DCC model, which allows long-range volatility dependence and an asymmetric response of volatility to positive and negative shocks. They specify the length and phases of different crises using both an economic and statistical approach (Markov Switching Dynamic Regression model). Based on different analyses over the time-varying correlations and the conditional variances obtained from the model, they find that the majority of the conditional correlations among currencies decline across the different phases, which indicates their varying degrees of vulnerability.

Similar approaches are used by Dimitriou et al. (2013) and Kenourgios (2014). Dimitriou et al. (2013) investigate the existence of contagion mechanism in the US stock market and the BRICS using a Bivariate AR(1)-FIAPARCH (1,d,1)-DCC model. Their findings support a general pattern of decoupling for some of the BRICS's markets at the early stages of the Global Financial Crisis, and a recoupling for almost all markets after the failure of Lehman Brothers.[2] Kenourgios (2014) investigates volatility contagion across U.S. and European stock markets during the Global Financial Crisis and the Eurozone Sovereign Debt Crisis by employing an AR-GJR-GARCH-A-DCC process. In this case the author finds a different pattern of infection across the phases, which are also specified by combining both an economic and statistical approach (where the VIX is used as an aggregate proxy for international risk.

Kenourgios et al. (2011) investigate contagion in a multivariate time-varying asymmetric framework focusing on the BRIC (once again the South African stock market is not considered), U.S. and U.K. stock markets on different financial crises. They confirm the existence of a contagion effect from each crisis country on all others.

On the basis of a DCC-GARCH model, Ahmad et al. (2013) analyze the time-varying cross market co-movements of GIPSI, U.S., U.K. and Japan markets on BRIICKS.[3] They find financial contagion of GIPSI on BRIICKS stock markets. Their results also show that Ireland, Italy and Spain appear to be the most contagious for BRIIKCS markets, compared to Greece.

[2] Other interesting studies are those of Hon et al. (2007), Syriopoulos and Roumpis (2009), Singh et al. (2010), and more recently Jacobs and Karagozoglu (2014) and Guidi and Ugur (2014).

[3] They are conscious that the usual acronym is BRICS but they include Indonesia and South Korea due to their strong economic and trade relations with the BRICS countries.

Samitas and Tsakalos (2013) use the A-DCC model and a copula function to analyze the correlation dynamics among the PIIGS and the U.K., France and Germany. They find that the subprime crisis increased the correlation between stock markets; however, the Greek crisis appears to have had a lower impact on the correlation among the markets.

More recently Liu et al. (2014) also analyze the PIIGS countries, focusing their objective on constructing optimal portfolio strategies. By assessing the historical performance of the Value at Risk-based equity portfolios, they demonstrate that there are limited diversification benefits because optimal portfolios are dominated by one index of each group they analyze, namely the Spanish IBEX-35 in the PIIGS case.

Despite the different approaches, this work follows the methodological line of Lee and Long (2009) and Harris and Mazibas (2013). Lee and Long (2009) proposed a new approach which they named C-MGARCH (Copula-based Multivariate GARCH) model, which permits modeling conditional correlation (by the multivariate GARCH) and dependence (by copula) separately and simultaneously, meanwhile Harris and Mazibas (2013) combine the Extreme Value Theory, which analyzes events that deviate sharply from the norm, and copulas.

3. Methodology

This section is divided into three main sub-sections. Firstly, we present the different multivariate GARCH models and our proposed approach. Secondly, we describe the methodology for the construction of the diversification portfolio. Finally, we describe the criterion employed to evaluate the performance of the alternative framework proposed.

3.1. Multivariate GARCH approaches

We initially use the DCC-GARCH framework, which will be enhanced by considering some improvements such as the asymmetries and copulas. These enhancements will lead us to the proposed Copula-ADCC-GARCH model, which solves the mentioned problems.

The Dynamic Conditional Correlation, DCC, GARCH model estimation is performed using a two-step approach. Firstly, a GARCH model for each time series was estimated, where the return generating process is conceptualized as:

$$\begin{aligned} r_{i,t} &= c_i + \sum_{\substack{i=1 \\ j=1}}^{5} \alpha_{ij} r_{i,t-1} + \varepsilon_{i,t} \\ \varepsilon_{it}|\Omega_{t-1} &\approx N(0, H_t) \end{aligned} \tag{1}$$

where $r_{i,t}$ are the daily returns for the PIIGS indexes, c_i and α_{ij} for i = 1, 2, 3, 4, 5, and j = 1, 2, 3, 4, 5, are the parameters to be estimated, H_t is a 5×5 matrix of time-varying covariances and $\varepsilon_{i,t}$ is a 5×1 vector of error terms which is assumed to be conditionally normal with zero mean and conditional variance matrix H_t. From each model the conditional variances, $h_{i,t}$, and the standardized residuals, $\delta_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}}$, are generated separately. In this model, it is very important to specify correctly the mean equation because its misspecification may lead to an incorrect estimation of the variance equation, as was pointed out by Ewing and Malik (2005).

Secondly, the conditional covariance matrix is specified as:

$$H_t = D_t R_t D_t \tag{2}$$

where $D_t = \text{diag}(\sqrt{h_{it}})$, is a diagonal matrix which contains the time-varying conditional volatilities of the previous GARCH models and R_t is a time-varying 5×5 correlation matrix with diagonal elements equals to 1 which is specified as:

$$R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1} \tag{3}$$

where $Q_t = \{q_{ij,t}\}$ is a covariance matrix of the standardized residuals denoted as:

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha(\delta_{t-1}\delta'_{t-1}) + \beta Q_{t-1} \tag{4}$$

$\overline{Q} = E[\delta_t \delta'_t]$ is the unconditional correlation matrix of the standardized residuals and $Q_t^* = \text{diag}(\sqrt{q_{ij,t}})$ is a diagonal matrix containing the square root of the diagonal elements of the $n \times n$ positive matrix Q_t. Finally, the parameters α and β are non-negative scalars such that $\alpha + \beta < 1$.

Therefore, the conditional correlation for a pair of markets i and j at time t can be defined as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \quad i, j = 1, 2, \ldots, 5, \text{ and } i \neq j \tag{5}$$

Under the Gaussian assumption, the log-likelihood of the estimators is:

$$L = -\frac{1}{2} \sum_{t=1}^{T} (n\log(2\pi) + 2\log|D_t| + \log|R_t| + \delta'_t R_t^{-1} \delta_t) \tag{6}$$

However, in the vast existing MGARCH literature there are two main criticisms of this DCC model. Firstly, the fact of not accounting for asymmetries in conditional variances, covariances and correlations could lead for an incorrect specification of the conditional variance-covariance matrix, as is pointed out by Cappiello et al. (2006) and de Goeij and Marquering (2009) among others. For that reason, we follow Cappiello et al. (2006) who proposed the Asymmetric DCC model (ADCC), which incorporated the leverage effect into the conditional correlations as follows:

$$Q_t = (1-\alpha-\beta)\overline{Q} - \gamma\bar{N} + \alpha(\delta_{t-1}\delta'_{t-1}) + \gamma\eta_{t-1}\eta'_{t-1} + \beta Q_{t-1} \tag{7}$$

where $\eta_t = I[\delta_t < 0] \odot \delta_t$ ($I[.]$ is a 5×1 indicator function which takes on value 1 if the argument is true and 0 otherwise while $\odot$ is the Hadamard product) and $\overline{N} = [\eta_t\eta'_t]$. Positive definiteness of Q_t is ensured by imposing that $\alpha + \beta + \lambda\gamma < 1$, where $\lambda =$ maximum eigenvalue $[\overline{Q}^{-1/2}\overline{N}\overline{Q}^{-1/2}]$.

The second problem is related to the distribution of the standardized residuals. They are supposed to be N(0, 1), however, that normal distribution is not consistent with the well-known skewness and excess kurtosis in this data.

This problem can be solved using the Copula approach which was proposed by Sklar (1959). The copula approach is described as follows: Let $\delta = (\delta_1, \delta_2, \ldots, \delta_n)$ be a vector of variables, i.d.d. standardized residuals series in our case, with marginal distributions $F_i(\delta_i)$, i = 1, ..., n, then the copula of δ_i is defined as the joint cumulative distribution function, CDF, of $F_i(\delta_i)$.

$$F(\delta_i) = F(\delta_1, \delta_2, \ldots, \delta_n) = C[F_1(\delta_1), \ldots, F_n(\delta_n)] \tag{8}$$

where C is a copula and $F_i(\delta_i)$ is a multivariate CDF.

Setting $u_i \equiv F_i(\delta_i)$ for notational convenience, the Gaussian copula is defined by the joint CDF:

$$C(u_1, u_2, \ldots, u_n; \rho) = \phi_\rho[\phi^{-1}(u_1), \ldots, \phi^{-1}(u_n)] \tag{9}$$

where ϕ_ρ is the joint CDF of a multivariate normal distribution with correlation ρ, $-1 < \rho < 1$, and ϕ^{-1} represents the inverse CDF of a standard normal.

Lee and Long (2009) proposed a new approach which they named C-MGARCH (Copula-based Multivariate GARCH) model. This methodology permits modeling conditional correlation (by the multivariate GARCH) and dependence (by copula) separately and simultaneously. As they pointed out, in order to estimate the C-MGARCH model, it is necessary to construct the joint CDF of the residuals from the first stage of the DCC approach and then use them to complete the second stage of the DCC model.

However, instead of using a symmetric approach for the DCC as Lee and Long (2009) do, we propose to employ an Asymmetric DCC (ADCC) after estimating the joint cumulative distribution function of the standardized residuals. This is why we named the model Copula ADCC-GARCH.

The joint CDF is estimated not by using the usual procedure for estimating the Gaussian copulas but following the procedure proposed by Harris and Mazibas (2013), who combine the Extreme Value Theory, which analyzes events that deviate sharply from the norm, and copulas, which model the co-movement of dependent variables whose probability distributions are different from each other and might not be normal, to estimate the CDF of each standardized residuals

Therefore, in order to add the copula approach to the ADCC-GARCH procedure we adopt the following four steps. Firstly, having index prices, we transform them to log returns. Then we filter the returns by fitting a VAR(1)-GARCH(1,1) model to the returns to get the residuals and standardize them. Secondly, we use a semi-parametric approach to estimate the CDF of the standardized residual series. We apply the Extreme Value Theory to the tails of the standardized residuals by using the Generalized Pareto Distribution and smooth the center of the CDF by estimating a Gaussian kernel. Thirdly, we combine the individual semiparametric CDFs estimated in the previous step to fit a multivariate Copula. In the next step, we use the estimated copula parameters to generate random numbers from the estimated joint cumulative distribution function. Then, we transform those numbers to the original scale of the standardized residuals using the inversion of the marginal of each standardized residuals. Finally, we introduce them in the ADCC model as the elements of δ_t and estimate the Copula-ADCC-GARCH with structural breaks model.

Finally, following Cappiello et al. (2006), we extend the model to allow for structural breaks. The break date is imposed on the basis of the ICSS algorithm developed by Inclan and Tiao (1994), and used by Aggarwal et al. (1999), Malik (2003), and Ewing and Malik (2005) among others.

The analysis assumes that the time series displays a stationary variance over an initial period until a sudden change in variance occurs. The variance is then stationary again for a time until the next sudden change. The process is repeated over time, yielding a time series of observations with an unknown number of changes in the variance.

Let ε_t be a series with zero mean and with unconditional variance σ_t^2. Let the variance within each interval be given by σ_j^2, j = 0, 1, ..., N_T where N_T is the total number of variance changes in T observations and $1 < \kappa_1 < \kappa_2 < \ldots < \kappa_{N_T} < T$ are the change points.

$$\begin{aligned} \sigma_t^2 &= \tau_0^2 \quad 1 < t < \kappa_1 \\ &= \tau_1^2 \quad \kappa_1 < t < \kappa_2 \\ &\quad \ldots \\ &= \tau_{N_T}^2 \quad \kappa_{N_T} < t < T \end{aligned} \tag{10}$$

To estimate the number of changes in variance and the point in time of each variance shift a cumulative sum of squares is used. Let $C_k = \sum_{t=1}^{k} \varepsilon_t^2, \quad k = 1, \ldots, T$, be the cumulative sum of the squared observations from the start of the series to the k-th point in time, where k is a point of sudden change and T is the number of observations. The D_k statistic is defined as follows,

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T} \quad k = 1, \ldots, T \quad D_0 = D_T = 0 \tag{11}$$

where C_T is the sum of the squared residuals from the whole sample period.

If there are no changes in variance over the sample period, the D_k statistic oscillates around zero (a horizontal line when plotted against k). However, if the series contains variance changes, the D_k values drift either above and below zero. Critical values based on the distribution of D_k under the null hypothesis of homogeneous variance provide upper and lower boundaries to detect a significant change in variance with a known level of probability. In this way, the null hypothesis of constant variance is rejected if the maximum absolute value of D_k is greater than the critical value. So, if $\max_k \sqrt{(T/2)}|D_k|$ exceeds the predetermined boundary, then the value of k is taken as an estimate of the change point. The critical value at the 95th percentile is 1.36, therefore the upper and lower boundaries can be set at ±1.36 in the D_k plot.

If the series under study has multiple change points, use of the D_k function alone is not sufficient to choose the correct change point due to "masking effects". To avoid this problem, Inclan and Tiao (1994) designed an algorithm that uses the D_k function to systematically look for change points at different points of the series.

Once the structural break is incorporated into the Copula-ADCC-GARCH model, we estimate the conditional correlation as follows:

$$Q_t = [(1-\alpha-\beta)\overline{Q}_1 - \gamma\overline{N}_1](1-d_t) + [(1-\alpha-\beta)\overline{Q}_2 - \gamma\overline{N}_2]d_t + \alpha(\delta_{t-1}\delta'_{t-1}) + \gamma\eta_{t-1}\eta'_{t-1} + \beta Q_{t-1} \tag{12}$$

where d_t is a dummy variable which takes on value 1, if $t \geqslant \kappa < T$ and 0 otherwise, $\overline{Q}_1 = E[\delta_t\delta'_t]$, $t < \kappa$, and $\overline{Q}_2 = E[\delta_t\delta'_t]$, $t \geqslant \kappa$, with $\overline{N}_1$ and $\overline{N}_2$ analogously defined.

3.2. Optimal portfolio

The main objective of this article is to use the forecasted returns and volatilities from the previous approaches to optimize different portfolios. To be precise, we propose to solve three optimization problems which minimize portfolio variances subject to different constraints.

The first optimization problem is the so called minimum-variance portfolio which is given by the following equation:

$$\min_{w_t} w'_t H_{t+1/t} w_t \tag{13}$$

where $w'_t H_{t+1/t} w_t$ is the portfolio risk equation to be minimized. We consider solving this optimization problem firstly, because risk or volatility is the main problem to solve when investing on PIIGS stock markets. Following that strategy, we are considering that the investor is exclusively interested on minimizing volatility. However, we know that in real life that is not true because they are also interested in getting profits from their investments.

Therefore, the second optimization problem is the classic mean-variance strategy proposed by Markowitz (1952). The goal of this optimization problem is also to minimize the portfolio risk but adding a target portfolio return constraint. Therefore, the optimization problem is given by:

$$\begin{aligned} &\min_{w_t} w'_t H_{t+1/t} w_t \\ &\text{subject to } w'_t E\{R_{t+1}\} \geqslant R^* \end{aligned} \tag{14}$$

where R^* denotes the desired target return performance. We use the equally weighted portfolio, also known as naïve portfolio, as the benchmark strategy following the same procedure as Christoffersen et al. (2014), Guidi and Ugur (2014), Hodrick and Zhang (2014) and Miralles-Marcelo et al. (2015). The use of this benchmark, where all the assets in the portfolio have the same weight, is justified on three grounds, as was pointed out by DeMiguel et al. (2009), Santos et al. (2012) and Guidi and Ugur (2014), among others. Firstly, this benchmark is easy to implement; secondly, it is widely used by international investors; and, finally, it has been proved that it outperforms other strategies.

As an alternative to the previous optimization problem, a target return of zero is considered for the third optimization problem, therefore it is more restrictive than the previous one. This optimization problem is given by the following equation:

$$\begin{aligned}&\min_{w_t} w_t' H_{t+1/t} w_t \\ &\text{subject to } w_t' E\{R_{t+1}\} \geqslant 0\end{aligned} \tag{15}$$

Following Santos et al. (2012), Harris and Mazibas (2013) and Guidi and Ugur (2014), who evaluate different optimization frameworks from a DCC-GARCH approach, short-sellings are excluded in the optimization problem by following the general constraints:

$$w_t'\mathbf{1} = 1 \quad w_i \geqslant 0 \quad i = 1, 2, \ldots, N \tag{16}$$

where w_i is the weight of each asset from the portfolio vector, $w_t = [w_1, w_2, \ldots, w_N]$, and $\mathbf{1}$ is a vector of ones.

Following the framework proposed by Santos et al. (2012), we use a rolling window of $\tau = 400$ to estimate the parameters of the models which are used for generating the expected returns and the conditional variance matrix[4]:

(1) Using the observations for $t = 1, \ldots, \tau$, estimate the DCC-GARCH and the Copula ADCC-GARCH with structural breaks models following the approach described previously.
(2) Forecast the expected returns $\mu_{\tau+1}$ and the conditional variance matrix $H_{\tau+1}$ from each model.
(3) Use the expected returns and the covariance matrix to solve the optimization problem and, therefore, obtain the portfolio weights w_τ for day $\tau + 1$.
(4) Compute the portfolio return as $r_{p,\tau+1} = w_\tau' r_{\tau+1}$, where $r_{\tau+1}$ is a vector of out-of-sample returns for day $\tau + 1$.
(5) Move to the next window with observations $t = 2, \ldots, \tau + 1$, and repeat steps 1 to 5. The number of total observations in our dataset, T, is 887 so we will obtain a total of $T - \tau = 447$ out of sample observations for the portfolio returns, conditional variances and covariances values derived from each procedure (DCC-GARCH and Copula ADCC-GARCH with structural breaks).

3.3. Performance evaluation

We evaluate the performance of the three optimization frameworks based on the DCC-GARCH and Copula-ADCC-GARCH approaches over the out of sample period $t = \tau + 1, \ldots, T$, in terms of the Sharpe ratio, SR_p.

The Sharpe ratio is defined as the average out-of-sample returns divided by their sample standard deviation:

$$SR_p = \frac{\overline{\mu}_p}{\sigma_p} \tag{17}$$

As reported by García and Luger (2011), it is necessary to consider this measure to evaluate portfolio performance because it is the most ubiquitous risk-adjusted measure used by financial market practitioners to rank fund managers and to evaluate the attractiveness of investment strategies in general.

Furthermore, to assess the statistical significance of the differences between the performance of the benchmark strategy (SR_{Naive}) and that of the model-based strategy (SR_p), we employ a bootstrap inference method. More precisely, the null hypothesis is $H_0 : \{SR_p - SR_{Naive} = 0\}$, for which we compute a one-sided *p*-value following the methodology proposed by Ledoit and Wolf (2008).

Additionally, to test whether our optimal portfolios produce economically significant profits, we calculate the portfolio performances after taking into account the costs associated with the daily rebalance of each portfolio considering not only transaction costs but also daily portfolio turnovers.

Following DeMiguel et al. (2009), we denote the share of wealth in area i before the portfolio is rebalanced at time t + 1 as:

$$\omega_{i,t^+} = \frac{\omega_{i,t}(1 + R_{i,t+1})}{\sum_{i=1}^{N} \omega_{i,t}(1 + R_{i,t+1})} \tag{18}$$

When the portfolio is rebalanced, it gives rise to a trade in area i of magnitude $|\omega_{i,t+1} - \omega_{i,t^+}|$, where $\omega_{i,t+1}$ is the optimal portfolio weight on area i at time t + 1 after rebalancing. Consequently, the total amount of turnover across all assets in the portfolio is:

$$\tau_{t+1} = \sum_{i=1}^{N} |\omega_{i,t+1} - \omega_{i,t^+}| \tag{19}$$

Moreover, if *c* denotes the proportional transactions cost, then the total cost to rebalance the portfolio is $c \times \tau_{t+1}$. Let $R_{p,t+1} = \sum_{i=1}^{N} R_{i,t+1}\omega_{i,t}$ denote the portfolio return from a given strategy before rebalancing occurs. The evolution of wealth invested according to that strategy is then given by:

$$W_{t+1} = W_t(1 + R_{p,t+1})(1 - c \times \tau_{t+1}) \tag{20}$$

[4] Santos et al. (2012) use approximately a 45% of the sample size (1000 observations over 2194 and 2154 observations) for constructing their rolling window. Once considered the same percentage over our database (887 observations) it yields 399.15 observations so we rounded it up to 400.

and the simple return net of rebalancing costs is $R^c_{p,t+1} = W_{t+1}/W_t - 1$. Since the portfolio $\mathbf{w}_t$ is formed using only information available at time t and held for one day before being rebalanced at time t + 1, the return $R^c_{p,t+1}$ represents the one-day out-of-sample return.

4. Database

The data used in this work are Wednesday-on-Wednesday returns from January 7, 1998 through December 2014 (amounting 887 usable observations) of the benchmark equity indices of the PIIGS countries, that is Portugal (PSI-20), Italy (FTSE MIB), Ireland (ISEQ-20), Greece (ASE) and Spain (IBEX-35). Weekly prices for a week running from Wednesday to Wednesday are used accordingly to Cappiello et al. (2006), Savva and Aslanidis (2010), Beirne et al. (2010), Yiu et al. (2010), You and Daigler (2010), and more recently Guidi and Ugur (2014), who put forward some reasons for it. Firstly, by using weekly returns cross-country, weekend effects are minimized; secondly, weekly returns are not as noisy as compared to the daily returns and, finally, because the use of weekly returns is more realistic for institutional diversification analysis compared to the daily or monthly returns.

The summary statistics of these stock index returns are reported in Table 1. We observe that only two out of five (ISEQ-20 and IBEX-35) show positive returns. However, on the basis of the Anova test, we cannot reject the null that all series in the group have the same mean since those differences are not statistically significant.

With respect to the standard deviation, we find that the Irish (ISEQ-20), Portuguese (PSI-20) and Spanish (IBEX-35) indexes possess the lowest values. In this case, the rejection of the null of equality of variances leads us to conclude that differences are statistically significant. Skewness and kurtosis values indicate that the distributions of returns for all the indexes are negatively skewed and leptokurtic. The Jarque–Bera statistic rejects the null hypothesis that the returns are normally distributed for all cases. The Ljung–Box statistic for up to 4 lags indicates the presence of significant linear and nonlinear dependencies in the returns of most of the indexes (there is just an exception for ISEQ). Finally, the ARCH test reveals that returns exhibit conditional heteroscedasticity in all series. These preliminary results point out that it is important to study more accurately the dynamics among these indexes.

In order to illustrate the differences among the five indexes, we show their return charts for the period analyzed in Fig. 1. We can clearly observe the existence of two different groups in these five countries. On the one hand we can consider that the PSI20, FTSE MIB, ISEQ-20 and IBEX-35 indexes behave in a similar way in terms of upward and downward movement. On the other hand we find a more volatile behavior pattern in the Greek index, ASE, in which those upward and downward trends are much more significant.

5. Empirical results

This section presents the empirical results for the models proposed and their economic implications in the calculation of a portfolio strategy. In the first stage of both multivariate DCC models, we assume that a VAR (1) approach is the best fitting specification for the mean equation following the Akaike information criterion. Additionally, using the methodology proposed by Inclan and Tiao (1994), we locate a structural break at the end of March 2003, which is incorporated into the Copula-ADCC-GARCH with structural break model. This structural break coincides with the minimum in all the PIIGS markets after the technological bubble crash of 2000. In the second stage, once the mean structure has been defined, both volatility and time-varying correlations are estimated for the DCC-GARCH and the Copula-ADCC-GARCH model with structural breaks models.

Table 2 displays the estimates of the model. In Panel A we show the estimated coefficients of the mean equations. We observe the existence of some significant dynamic relationships among the indexes. In Panel B we observe that the coefficients in the variance equations are mostly significant for the five indexes. Dynamic correlations in the markets are supported by the significant coefficients of α, β and γ in Panels C and D. Moreover, the significance of γ confirms the appropriateness of the Copula-ADCC-GARCH model with structural breaks. Finally, from the value of the LR statistic, which is asymptotically χ^2 distributed and is shown in Panel E, we can clearly reject the null of no asymmetric effects even at the 1% significance level.

Table 3 reports the out-of-sample performance results of the optimal portfolios based on both DCC-GARCH and Copula ADCC-GARCH with structural breaks approaches, as well as those relative to the naïve strategy which is used as the benchmark.

Panel A shows the results for the minimum variance strategy, Panel B those for the mean-variance strategy with the portfolio return constraint of outperforming the naïve portfolio return and Panel C reports those relative to the mean-variance strategy with the portfolio return constraint of being non negative. Returns and standard deviations are reported in annualized terms and percentage. We can clearly obtain three main conclusions from these results. Firstly, benefits of diversification are evident because the three proposed strategies outperform the naïve strategy in terms of Sharpe ratio. Secondly, we show evidence that when asymmetries, copulas and structural breaks are taken into account, the performance results are clearly improved. Finally, based on the results of the Sharpe ratio, the best strategy is the mean variance strategy (Naïve) when it is based on the Copula ADCC-GARCH approach. Although return predictability has usually been neglected in financial literature and researchers have primarily focused on analyzing the economic value of the minimum variance strategy, our

Table 1
Descriptive statistics.

	PSI-20	FTSE MIB	ISEQ-20	ASE	IBEX-35	Equality test
Mean	$-6.84{\cdot}10^{-4}$	$-2.81{\cdot}10^{-4}$	0.001	$-6.57{\cdot}10^{-4}$	$3.93{\cdot}10^{-4}$	0.482 (0.748)
Std. Dev.	0.030	0.033	0.029	0.043	0.032	180.764 (0.000)
Skewness	−0.545	−0.407	−0.659	−0.135	−0.363	
Kurtosis	6.510	4.853	5.652	4.223	4.559	
Jarque-Bera	499.440 (0.000)	151.548 (0.000)	324.266 (0.000)	58.080 (0.000)	109.457 (0.000)	
Q (4)	8.006 (0.091)	15.177 (0.004)	1.337 (0.855)	8.485 (0.075)	9.528 (0.049)	
Q^2 (4)	72.030 (0.000)	112.84 (0.000)	69.991 (0.000)	62.153 (0.000)	133.18 (0.000)	
ARCH (4)	50.485 (0.000)	86.781 (0.000)	55.133 (0.000)	46.553 (0.000)	102.92 (0.000)	

This table presents descriptive statistics for the weekly return series of the PSI-20, FTSE MIB, ISEQ-20, ASE and IBEX-35 indexes for the sample period from January 7, 1998 through December 31, 2014. The last column reports the mean and variance equality tests using the ANOVA and Levene statistics, respectively. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera statistic tests the normality of the series. This statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. Q (4) and Q^2 (4) are Ljung–Box tests for 4th-order serial correlation in the returns and squared returns. ARCH (4) is the Engle (1982) test for the 4th-order ARCH. These three tests are distributed as $\chi^2(4)$. The p values of these tests are reported in parenthesis

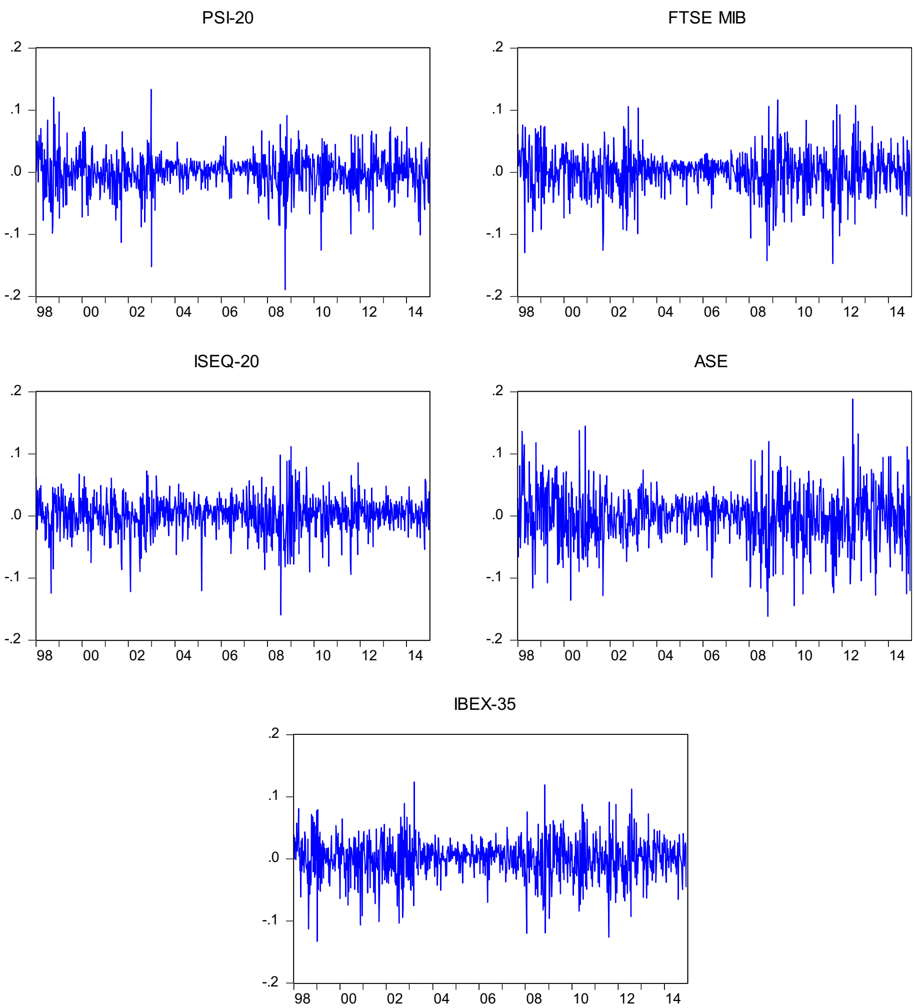

Fig. 1. Returns of the stock indexes.

Table 2
Estimates from the DCC and Copula-ADCC with structural breaks models.

	PSI coeff.	p-value	MIB coeff.	p-value	ISEQ coeff.	p-value	ASE coeff.	p-value	IBEX coeff.	p-value
Panel A: Mean equations										
c_i	$1.42{\cdot}10^{-4}$	(0.87)	$7.35{\cdot}10^{-4}$	(0.53)	0.002^{**}	(0.07)	0.001	(0.19)	0.001	(0.11)
$R_{PSI,t-1}$	−0.006	(0.92)	0.074	(0.23)	0.113^{**}	(0.07)	0.063	(0.34)	−0.008	(0.90)
$R_{MIB,t-1}$	0.149^{**}	(0.07)	0.010	(0.91)	0.032	(0.67)	0.078	(0.46)	−0.029	(0.79)
$R_{ISEQ,t-1}$	0.012	(0.78)	0.066	(0.17)	0.051	(0.22)	0.028	(0.60)	0.111^{**}	(0.05)
$R_{ASE,t-1}$	−0.010	(0.80)	0.006	(0.88)	−0.002	(0.93)	0.041	(0.45)	−0.008	(0.85)
$R_{IBEX,t-1}$	−0.066	(0.41)	−0.117	(0.18)	0.022	(0.80)	0.011	(0.90)	−0.089	(0.37)
Panel B: GARCH parameters										
c_i	$1.38{\cdot}10^{-5}$	(0.17)	$2.27{\cdot}10^{-5}$	(0.18)	$6.69{\cdot}10^{-4***}$	(0.00)	$-4.45{\cdot}10^{-6**}$	(0.06)	$1.06{\cdot}10^{-5}$	(0.22)
$\varepsilon^2_{i,t-1}$	0.167^{***}	(0.00)	0.170^{***}	(0.00)	0.308^{***}	(0.00)	−0.014	(0.39)	0.125^{***}	(0.00)
$h^2_{i,t-1}$	0.829^{***}	(0.00)	0.819^{***}	(0.00)	0.135^{***}	(0.00)	1.013^{***}	(0.00)	0.872^{***}	(0.00)
Panel C: DCC persistence parameters										
α	0.050^{***}	(0.00)								
β	0.899^{***}	(0.00)								
Panel D: Copula-ADCC with structural breaks persistence parameters										
α	0.040^{***}	(0.00)								
β	0.919^{***}	(0.00)								
γ	0.019^{***}	(0.00)								
Panel E: LR Statistic										
LR	3715.322									

This table reports the estimations from both the DCC-GARCH and Copula-ADCC-GARCH with structural breaks models. Panel A shows the mean equations for the indexes returns series (p-values in parenthesis). Panel B shows the variance equations (p-values in parenthesis). Panels C and D report the persistence parameters of both models and, finally, Panel E shows the LR test statistic. ***, ** and * represent the levels of significance of 1%, 5% and 10%, respectively.

Table 3
Out-of-sample performance evaluation.

	Naïve	DCC-GARCH	Copula ADCC-GARCH with structural breaks
Panel A: Minimum Variance			
Return	−0.037	0.003	0.005
SD	0.214	0.187	0.199
Sharpe ratio	−0.174	0.017	0.025
p value $H_0 : \{SR_p - SR_{Naive} = 0\}$		(0.000)	(0.000)
Panel B: Mean-Variance (Naïve)			
Return	−0.037	0.009	0.015
SD	0.214	0.187	0.203
Sharpe ratio	−0.174	0.047	0.077
p value $H_0 : \{SR_p - SR_{Naive} = 0\}$		(0.000)	(0.000)
Panel C: Mean-Variance (Positive)			
Return	−0.037	0.008	0.007
SD	0.214	0.183	0.200
Sharpe Ratio	−0.174	0.042	0.035
p value $H_0 : \{SR_p - SR_{Naive} = 0\}$		(0.000)	(0.000)

This table reports the out-of-sample performance evaluation of the proposed portfolios based on the annualized mean, the annualized standard deviation and the annualized Sharpe ratios with the resulting bootstrap p-values reported in parenthesis obtained using the methodology suggested in Ledoit and Wolf (2008).

results reveal that return predictability is of considerable interest. As Marquering and Verbeek (2004) argue, any predictability in expected returns is accompanied by a change in the conditional variance. Moreover, the exploitation of both sources of predictability results in investment strategies that outperform strategies which exploit only one source.

The mean portfolio weights for each index following the different procedures are reported in Table 4.

From those results we can point out some interesting conclusions. Firstly, the mean optimal weight of the Irish stock market benchmark index is mostly higher than the others using both procedures, mainly because it is the one with higher mean return and lower volatility. Secondly, the three indexes with lower volatility (ISEQ-20, PSI-20 and IBEX-35) result in a weight higher than 80% using both DCC-GARCH and Copula ADCC-GARCH approaches. For example, focusing on the best strategy as reported previously, that entitled Mean Variance (Naïve), they amount to 85.01% of the total weight when the DCC-GARCH approach is used and 90.98% when the Copula ADCC-GARCH with structural breaks is considered. It must also be pointed out that the total weight of these three indexes is higher when the strategies are based on the Copula ADCC-GARCH with structural breaks approach because, in our opinion, this approach better fits the indexes. Finally, one of the main fears that

Table 4
Mean weekly portfolio weights.

	PSI-20	FTSE MIB	ISEQ-20	ASE	IBEX-35
Naïve	20%	20%	20%	20%	20%
Panel A: DCC-GARCH					
Minimum Variance	31.39%	8.98%	40.04%	5.99%	13.57%
Mean-Variance (Naïve)	28.32%	7.37%	40.51%	6.42%	15.76%
Mean-Variance (Positive)	28.57%	7.73%	37.79%	6.04%	15.12%
Panel B: Copula ADCC-GARCH with structural breaks					
Minimum Variance	39.64%	7.33%	39.47%	1.48%	12.08%
Mean-Variance (Naïve)	33.56%	6.02%	42.28%	3.00%	15.14%
Mean-Variance (Positive)	26.27%	5.74%	37.91%	1.63%	28.46%

This table reports the mean weekly portfolio weights for the naïve strategy (equally weighted) and those obtained from solving the optimization problems where the time-varying returns and volatility forecasts from the DCC-GARCH and Copula ADCC-GARCH are used.

investors could have of investing in these stock markets is derived from the Greek economic instability. However, we can observe that the weight of the Greek stock index is low in the strategies which are based on the DCC-GARCH model. Additionally, once the copulas, asymmetries and structural breaks are taken into account with the Copula ADCC-GARCH with structural breaks approach, this weight is reduced to the minimum.

To give additional support to the best performance of the Copula ADCC-GARCH based portfolio, Fig. 2 displays its cumulative returns as well as the benchmark portfolio over the out-of-sample period.

We observe that these cumulative returns are mostly positive and far higher than the benchmark portfolio, which are mostly negative. Additionally, we find a significant upward trend at the end of the sample which coincides with the most volatile period in these markets, especially for the Greek index. The reduced weight of the Greek index in the mean optimal portfolio also explains the fact of having positive cumulative returns in the most volatile periods.

In order to check the robustness of the previous results, we calculate the portfolios performance considering two different transaction costs: 1 basis point and 3 basis points. Results are reported in Tables 5 and 6.

As we observe, the results provide two relevant conclusions. Firstly, the strategy based on the Copula ADCC-GARCH with structural breaks approach clearly outperforms the benchmark (naïve) and that based on a DCC-GARCH approach in all cases. Secondly, even when a 3 basis points transaction cost is considered the Sharpe ratio values are positive for the mean variance (naïve) strategy based on the Copula ADCC-GARCH with structural breaks approach while those referred to the other approaches are negative. Therefore, these results prove that the best strategy is the mean variance (naïve) which is based on the Copula ADCC-GARCH approach.

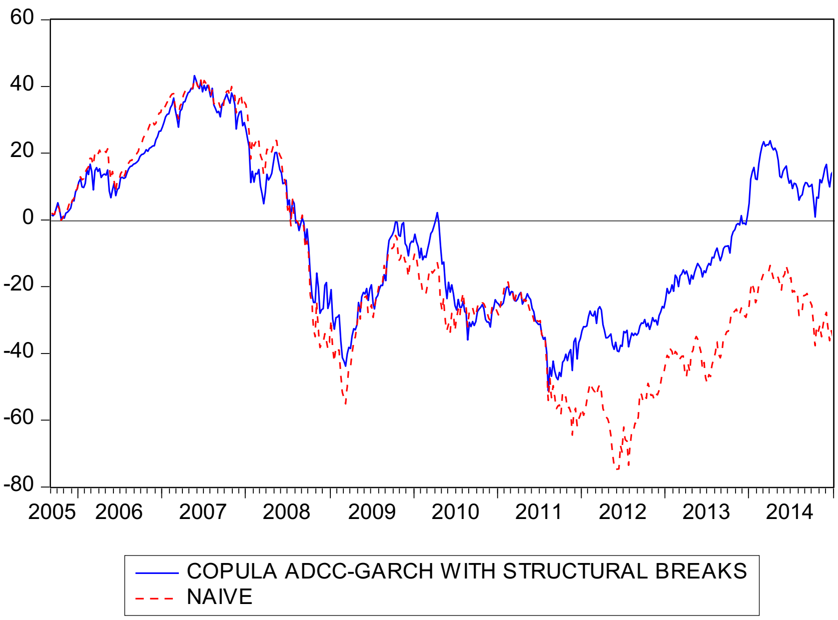

Fig. 2. Cumulative returns. This figure displays the cumulative returns over the out-of-sample period of the naïve strategy as well as the best performing strategy, Mean-Variance (Naïve), based on the use of time-varying returns and volatility forecasts from a Copula ADCC-GARCH with structural breaks approach.

Table 5
Out-of-sample performance evaluation after transaction costs (1 bp).

	Naïve	DCC-GARCH	Copula ADCC-GARCH with structural breaks
Panel A: Minimum Variance			
Return	−0.039	0.000	0.001
SD	0.214	0.188	0.200
Sharpe ratio	−0.184	0.001	0.005
p value $H_0 : \{SR_p - SR_{Naive} = 0\}$		(0.000)	(0.000)
Panel B: Mean-Variance (Naïve)			
Return	−0.039	0.005	0.011
SD	0.214	0.187	0.203
Sharpe ratio	−0.184	0.027	0.052
p value $H_0 : \{SR_p - SR_{Naive} = 0\}$		(0.000)	(0.000)
Panel C: Mean-Variance (Positive)			
Return	−0.039	0.004	0.002
SD	0.214	0.183	0.201
Sharpe ratio	−0.184	0.021	0.009
p value $H_0 : \{SR_p - SR_{Naive} = 0\}$		(0.000)	(0.000)

This table reports the out-of-sample performance evaluation of the proposed portfolios based on the annualized mean, the annualized standard deviation and the annualized Sharpe ratios with the resulting bootstrap p-values reported in parenthesis obtained using the methodology suggested in Ledoit and Wolf (2008) and considering a transaction cost of 1 basis point.

Table 6
Out-of-sample performance evaluation after transaction costs (3 bp).

	Naïve	DCC-GARCH	Copula ADCC-GARCH with structural breaks
Panel A: Minimum Variance			
Return	−0.041	−0.003	−0.005
SD	0.214	0.188	0.200
Sharpe ratio	−0.191	−0.016	−0.025
p value $H_0 : \{SR_p - SR_{Naive} = 0\}$		(0.000)	(0.000)
Panel B: Mean-Variance (Naïve)			
Return	−0.041	0.000	0.003
SD	0.214	0.187	0.203
Sharpe ratio	−0.191	0.002	0.015
p value $H_0 : \{SR_p - SR_{Naive} = 0\}$		(0.000)	(0.000)
Panel C: Mean-Variance (Positive)			
Return	−0.041	−0.001	−0.006
SD	0.214	0.183	0.201
Sharpe ratio	−0.191	−0.006	−0.032
p value $H_0 : \{SR_p - SR_{Naive} = 0\}$		(0.000)	(0.000)

This table reports the out-of-sample performance evaluation of the proposed portfolios based on the annualized mean, the annualized standard deviation and the annualized Sharpe ratios with the resulting bootstrap p-values reported in parenthesis obtained using the methodology suggested in Ledoit and Wolf (2008) and considering a transaction cost of 3 basis points.

These results are consistent with those reported by Thorp and Milunovich (2007) and Zhou and Nicholson (2015) among others who show that modeling covariance asymmetry yields significant economic value. Additionally, it must be pointed out that the out of sample period used covers a mix of bearish and bullish markets. We find high volatilities and negative returns that would lead investors to reduce their exposure to stock markets. We can see, however, that in the theoretically riskier markets, those known as PIIGS, the Copula-ADCC-GARCH with structural breaks yields not only higher returns but also better Sharpe ratios.

6. Conclusions

The objective of this article has been the analysis of different portfolio strategies for the PIIGS stock markets. This analysis is based on the return and volatility forecasts of two multivariate GARCH approaches: the DCC-GARCH and the Copula ADCC-GARCH with structural breaks, which nests the former.

From the initial results, the best strategy for investing on the PIIGS stock markets is the mean variance strategy with the portfolio return constraint of outperforming the naïve portfolio return. That strategy is estimated on the basis of the return and volatility forecasts from a Copula ADCC-GARCH with structural breaks approach. We show that strategy clearly outperforms the naïve diversification strategy, as well as two other portfolio strategies which are considered as alternatives. These results are also robust for the presence of transaction costs.

These findings appeal to both fund managers and their investor clientele because higher risk-adjusted returns are obtained, due to the positive Sharpe ratio, and the economic value is sufficient to cover transaction costs or management fees. To sum up, it has been proven that investing in the PIIGS markets is profitable and that there should not be any fear of investing in these theoretically troubled countries because PIIGS can fly.

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